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Maij - de Meij, A.M.; Kelderman, H.; van der Flier, H.

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Latent-Trait Latent-Class Analysis of Self-Disclosure in the Work Environment

Annette M. Maij-de Meij, Henk Kelderman,
and Henk van der Flier
Free University Amsterdam

Based on the literature about self-disclosure, it was hypothesized that different groups of subjects differ in their pattern of self-disclosure with respect to different areas of social interaction. An extended latent-trait latent-class model was proposed to describe these general patterns of self-disclosure. The model was used to analyze the data of 1,113 subjects, tested on extraversion and with respect to their degree of self-disclosure toward different categories of people in the work environment. A model with one latent trait and a latent class variable with three categories was identified. Subjects belonging to the different latent classes differ in their general tendency to self-disclose, in their choice to whom they will show self-disclosure and in the degree to which they are selective in their self-disclosure. The collateral variable extraversion was associated with both latent variables. The association of extraversion with selectivity in self-disclosure was not significant.

The concept of *self-disclosure* has had a long history. Jourard and Lasakow (1958) refer to self-disclosure as “the process of making the self known to other persons.” Cozby (1973) defines self-disclosure as “any information about himself which person A communicates verbally to person B.” According to Cozby (1973) and Omarzu (2000) self-disclosure consists of three basic dimensions. The first is the breadth or amount of information disclosed, referring to the num-

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Correspondence concerning this article should be addressed to Annette M. Maij-de Meij, Faculty of Psychology and Pedagogics, Van der Boechorststraat 1, 1081 BT Amsterdam, The Netherlands. E-mail: am.maij-de.meij@psy.vu.nl

ber of topics covered by the disclosure. The depth or intimacy of the information disclosed is the second dimension. The third is the duration or time spent describing each item of information.

Jourard was one of the first researchers who operationalized self-disclosure. In collaboration with Lasakow he developed the Self-Disclosure Questionnaire (SDQ; Jourard & Lasakow, 1958). Jourard intended to use the scale to identify the larger social patterns of disclosure content, as well as individual, trait-like differences in self-disclosure tendencies. He conjectured that differences in self-disclosure are determined above all by stable personality differences (Jourard, 1971).

Self-disclosure has been studied not only as a personality construct but also as a behavioral process occurring during interaction with others. Aspects of this process, such as reciprocity and social exchange, have been studied extensively (Cozby, 1973; Morton, 1978; Rubin, 1975). These aspects have to do with the development of social relationships (Cozby, 1973). Altman and Taylor (1973) developed the social penetration model. This model describes how social relationships between strangers develop from casual acquaintanceships to close personal friendships. Other studies focused on who elicits self-disclosure from others (Colvin & Longueuil, 2001; Miller, Berg, & Archer, 1983). In this article, self-disclosure is seen from the perspective of a personality construct. It is studied whether there are qualitative individual differences in self-disclosure patterns.

Self-disclosure is often found to be related to extraversion. Several studies show the degree of self-disclosure to be correlated to personality measures. See Cozby (1973) for an overview. *Extraversion* can be defined as the degree to which one's energy, attention and orientation is directed outwards. An extravert person is someone who is not shy and prefers to spend time with other people rather than alone, and who has an active involvement with the environment. Introvert people, on the other hand, have more negative expectations about social interactions, which can lead to social avoidance. They tend to be on their own and to withdraw into themselves (Carver & Scheier, 1995; Morris, 1979).

DISCLOSURE DECISION MODEL

Omarzu (2000) developed the *Disclosure Decision Model* for the processes that determine the specific dimensions of individuals' disclosure. Whether any self-disclosure will be made in a given situation depends on the presence of social goals. These goals can be social rewards that one can achieve through self-disclosure. Which goal is important to someone, depends on the individual. Also, situational cues must highlight the salience of the particular social reward.

Next, it is decided whether self-disclosure is an appropriate strategy to exercise and to whom one will disclose, otherwise the self-disclosure strategy has no satisfactory goal utility (Miller & Read, 1987; Omarzu, 2000).

The final decision has to be made regarding precisely what to disclose. The model assumes that people evaluate the utility of disclosure rewards as well as the risks of self-disclosure. These risks include, among others, social rejection, betrayal, and causing discomfort to the listener (Omarzu, 2000). Omarzu hypothesized that, "As subjective risk increases, the depth of disclosure will decrease. ... Even when the subjective utility of the goal is high, perceived risk should decrease the emotional intensity of disclosures" (p. 180).

This is in agreement with Steel's (1991) finding that interpersonal trust and self-disclosure are positively related. When people trust others and do not feel they can be hurt easily, then they will show self-disclosure. These people do not see much risk in self-disclosure because they are less suspicious and prejudiced than people who do not trust others that easily. Therefore, their self-disclosure is often deep and more intimate (Omarzu, 2000). Because more extravert people have less suspicion toward others and feel more interpersonal trust, it can be expected that they have a greater tendency to disclose themselves to others. Furthermore, because they are about equally open to different categories of people, their trust depends on their personality rather than on the person in front of them. Therefore, it is expected that they will be less selective in the person to whom they will self-disclose. On the other hand, introvert people see much risk in self-disclosure; they have negative expectations about social interaction. They will be less trusting and will not show much self-disclosure. Also, they will be more selective in their choice to whom they will show self-disclosure.

The Disclosure Decision Model leads to the introduction of the concept of selectivity in self-disclosure. This would be an extension of the literature on self-disclosure by drawing attention to situational specificity. In this study situational specificity concerns the person the subject is facing. If the subject doesn't know a person, possible prejudice and suspicion will be based on rough social categories (Vonk, 1999). In the work environment these categories are primarily: employees, colleagues, superiors, and customers. Because the prejudices are stable over time, selectivity in self-disclosure with respect to these categories of people will also be stable over time.

To determine to what extent people are selective in their self-disclosure, one has to look at the differences in their self-disclosure toward different (groups of) people to which they are exposed. When differences in self-disclosure with respect to the different categories of people are small, it means that the person is equally open and will take an equally vulnerable position toward the different categories of people. To these subjects it doesn't matter who they are facing,

they are not selective in their self-disclosure. When the differences in self-disclosure are large, it indicates that it matters to the person who (s)he is facing. This person is not equally open to everybody but is more selective in the choice to whom (s)he will show self-disclosure.

In summary, it can be expected that there is an overall tendency to self-disclose that is reflected in different areas of social interaction. It is hypothesized, however, that different groups of subjects differ in their pattern of self-disclosure with respect to the different areas of social interaction. Subjects who respond differently to the different (groups of) people are selective in their self-disclosure. So, different response patterns of self-disclosure may reflect differences in selectivity in self-disclosure. It is expected that there are qualitative individual differences with respect to self-disclosure reflecting differences in selectivity in self-disclosure (Hypothesis 1). In this article, mixture measurement models are specified to test whether sub-populations can be distinguished, that have qualitative different response patterns.

Hypothesis 2 concerns the relationship between extraversion and self-disclosure. It is expected that people who are extravert will show more self-disclosure than introvert people (a). Concerning selectivity in self-disclosure, it is expected that in comparison to introvert people, extravert people are less selective in their self-disclosure (b). In the next section a model is developed that is suitable to determine subgroups with different patterns of self-disclosure but also allows self-disclosure responses to be associated within each subgroup.

GENERAL MODELING FRAMEWORK

The general modeling framework is an extension of mixture measurement models introduced by Rost (1990, 1991), Kelderman and Macready (1990), Mislevy and Verhelst (1990) and Heinen (1996). First, associations between the responses are modeled with Bock's (1972) nominal response model. The model is written as a latent-class association model, where the continuous latent trait is made discrete (Heinen, 1996). Bock's nominal response model assumes that the responses of all subjects in the population of interest are governed by the same measurement model. However, since the primary interest is in detecting subgroups of subjects that show different patterns of self-disclosure with respect to the recipient of the disclosure, we propose a mixture model. The mixture components correspond to the subgroups, and the patterns of difficulty parameters in Bock's model correspond to patterns of self-disclosure. The model is parameterized such that the latent trait takes care of the common variation of responses within each mixture component. In the sequel, the mixture components are called latent classes and the quantitative latent variable of Bock's nominal re-

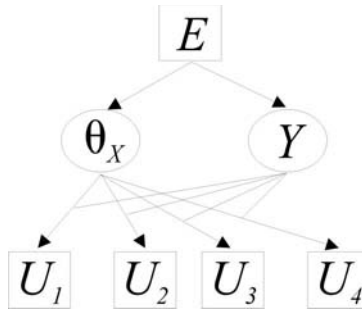


FIGURE 1 Discrete recursive graphical model with variables extraversion, E , latent trait, θ_X , mixture component, Y , self-disclosure toward employees, U_1 , colleagues, U_2 , superiors, U_3 , and customers, U_4 .

sponse model is the “latent trait.” Finally, to study whether extraversion is associated with self-disclosure, the model is extended with a collateral variable that is exogenous with respect to the latent variables. The final model is a discrete recursive graphical model (Cox & Wermuth, 1996; Lauritzen, 1996) containing latent variables. Figure 1 depicts the graphical model for the self-disclosure data. The arrows denote a regression, the squares represent the manifest variables, while the ellipses represent the latent variables. The latent class variable is allowed to influence the difficulty parameter for the relation between the self-disclosure responses and the latent trait.

First, the relations between the latent variables and the self-disclosure responses are modeled. Let θ denote a latent trait value describing the degree to which a subject possesses the attribute of interest. Furthermore, let U_i denote a subject’s response to item i ($i = 1, \dots, k$) taking values $u_i = 1, \dots, m_i$. Bock’s (1972) nominal response model (NRM) describes the probability of u_i given θ as

$$P(U_i = u_i | \theta) = \frac{\exp(c_{iu_i} + a_{iu_i}\theta)}{\sum_{h=1}^{m_i} \exp(c_{ih} + a_{ih}\theta)}, \quad (1)$$

where the intercept c_{iu_i} and slope a_{iu_i} are restricted to sum to zero over the responses. In item response theory models, the slope parameter is called the “discrimination” parameter, and the category intercept is called the “difficulty” parameter. The denominator is a constant of proportionality which ensures that the probabilities sum to one over the item responses. The NRM can be re-formulated as a row-column association model (Goodman, 1979; Heinen, 1996).

First write Equation 1 as a loglinear model, that is,

$$\log P(U_i = u_i | \theta) = d + c_{iu_i} + a_{iu_i} \theta, \quad (2)$$

where d is $-\log$ the proportionality constant. The slope parameter is re-parameterized as,

$$a_{iu_i} = \tau_{u_i}^{U_i} \xi^{U_i \theta}, \quad (3)$$

such that $\tau_{u_i}^{U_i}$ satisfies both

$$\sum_{u_i=1}^{m_i} \tau_{u_i}^{U_i} = 0,$$

and

$$\sum_{u_i=1}^{m_i} \left(\tau_{u_i}^{U_i} \right)^2 = 1. \quad (4)$$

From Equations 3 and 4 one has

$$\begin{aligned} \xi^{U_i \theta} &= \left[(1 \xi^{U_i \theta})^2 \right]^{1/2} = \left[\sum_{u_i=1}^{m_i} \left(\tau_{u_i}^{U_i} \right)^2 (\xi^{U_i \theta})^2 \right]^{1/2} \\ &= \left[\sum_{u_i=1}^{m_i} \left(\tau_{u_i}^{U_i} \xi^{U_i \theta} \right)^2 \right]^{1/2} = \left(\sum_{u_i=1}^{m_i} a_{iu_i}^2 \right)^{1/2}, \end{aligned} \quad (5)$$

where the second equation follows from Equation 4 and the fourth equation follows from Equation 3. The parameter $\xi^{U_i \theta}$ describes the overall association between the response to item i and the latent trait, while the parameter $\tau_{u_i}^{U_i}$ represents a category score for the response u_i . If it is assumed that subjects are randomly selected from a population with distribution $f(\theta)$, one has from Equations 2 and 3

$$\begin{aligned} \log P(U_i = u_i, \theta) &= \log [P(U_i = u_i | \theta) f(\theta)] \\ &= d + \log f(\theta) + c_{iu_i} + \tau_{u_i}^{U_i} \xi^{U_i \theta}. \end{aligned}$$

The distribution $f(\Theta)$ can be approximated to any degree of accuracy by a discrete distribution $g(\theta_X)$, where X is a nominal variable with categories $x = 1, \dots, r$, and θ_x is a fixed metric score assigned to category x . For simplicity, it is assumed that the scores θ_x have equal distances (Heinen, 1996). The joint loglinear model for the discrete latent trait variable and the item responses now becomes

$$\begin{aligned}\log P(U_i = u_i, \theta_X = \theta_x) &= \log \left[P(U_i = u_i | \theta_X = \theta_x) g(\theta_X = \theta_x) \right] \\ &= \lambda + \lambda_x^X + \lambda_{u_i}^{U_i} + \mu_{u_i}^{U_i} \phi^{U_i X} \theta_x,\end{aligned}\quad (6)$$

For simplicity, from here on the superscripts will be omitted, except where needed. The parameter λ_{u_i} denotes the item difficulty parameter. The superscripts of the association parameter, $\phi^{U_i X}$, are markers, indicating the variables for which the association is defined. To obtain estimable category scores, the item category scores μ_{u_i} are restricted to satisfy

$$\sum_{u_i=1}^{m_i} \mu_{u_i} = 0, \quad \text{and} \quad \sum_{u_i=1}^{m_i} \mu_{u_i}^2 = 1.$$

The category scores scale the categories of the items and provide information about the distances between the response categories. The odds ratio of the distances between the response categories gives information about the intervals between the categories. By estimating the item category scores, no assumptions have to be made with respect to the ordering of the categories of the manifest variables. If they are properly ordered, this will be reflected in their estimated values (Clogg, 1982; Goodman, 1979). Without loss of generality, the latent trait scores are fixed in advance and chosen to satisfy

$$\sum_{x=1}^r \theta_x = 0, \quad \text{and} \quad \sum_{x=1}^r \theta_x^2 = 1.$$

Finally, if the main effect of the latent trait is parameterized to sum to zero over the index, then it relates to the distribution $g(\theta_X = \theta_x)$ by

$$\lambda_x = \log g(\theta_X = \theta_x) - r^{-1} \sum_{x=1}^r \log g(\theta_X = \theta_x).$$

The Model shown by Equation 6 is a latent trait model where the observed self-disclosure responses are related to the discrete latent trait via a row-association model (Goodman, 1979). The model is easily extended to a mixture la-

tent-trait latent-class model by adding a latent class variable Y , where the values y represent the mixture components,

$$\begin{aligned} \log P(U_i = u_i, \theta_X = \theta_x, Y = y) \\ &= \log [P(U_i = u_i | \theta_X = \theta_x, Y = y) g(\theta_X = \theta_x) P(Y = y)] \\ &= \lambda + \lambda_x + \lambda_y + \lambda_{u_i} + \lambda_{u_i y} + \mu_{u_i} \phi^{U_i X} \theta_x, \end{aligned} \quad (7)$$

with additional identifying restrictions, $\sum_y \lambda_y = 0$ and $\sum_y \lambda_{u_i y} = \sum_{u_i} \lambda_{u_i y} = 0$. The general mean is denoted by λ , whereas the main effects of the discrete latent trait, the latent class and the self-disclosure responses u_i are represented by λ_x , λ_y , and λ_{u_i} , respectively. The parameter $\lambda_{u_i y}$ describes the interaction of self-disclosure score u_i and latent class membership. Note that the sum $\lambda_{u_i} + \lambda_{u_i y}$ is equal to the class specific difficulty parameter of response u_i in the nominal response model shown by Equation 1. The model term $\lambda_{u_i y}$ describes the between class differences, whereas the term $\mu_{u_i} \phi^{U_i X} \theta_x$ describes the individual differences in self-disclosure responses within each class. The association between the response to item i and the latent trait is described by the parameter $\phi^{U_i X}$.

The Model shown by Equation 7 describes the relations between self-disclosure responses and the latent variables. That is the lower half of Figure 1. In the upper half of this figure, the collateral variable extraversion is related to the latent variables. Both latent class membership and the distribution of the latent trait are specified conditional on the collateral variable. Extraversion is related to the item responses via the latent variables.

A row-column association model is formulated to model the relation between the latent-class variable and extraversion, while the relation with the discrete latent trait is specified by a row-association model (Goodman, 1979). Adding these associations, as well as a main effect of extraversion, the joint loglinear model for all latent and manifest variables becomes,

$$\begin{aligned} \log P(U_i = u_i, \theta_X = \theta_x, Y = y, E = e) \\ &= \log [P(U_i = u_i | \theta_X = \theta_x, Y = y) g(\theta_X = \theta_x | E = e) P(Y = y | E = e) P(E = e)] \\ &= \lambda + \lambda_x + \lambda_y + \lambda_e + \lambda_{u_i} + \lambda_{u_i y} + \mu_e \phi^{XE} \theta_x + \nu_e \phi^{YE} \mu_y + \mu_{u_i} \phi^{U_i X} \theta_x, \end{aligned} \quad (8)$$

with additional identifying restrictions $\sum_e \lambda_e = 0$, $\sum_e \mu_e = \sum_e \nu_e = \sum_y \mu_y = 0$ and $\sum_e \mu_e^2 = \sum_e \nu_e^2 = \sum_y \mu_y^2 = 1$. The category score of extraversion in the relation to the latent trait is denoted by μ_e , whereas the category scores in the relation between extraversion and the latent classes are represented by ν_e and μ_y , for extraversion and the latent classes respectively. Furthermore, the association parameters ϕ^{XE} and ϕ^{YE} describe the association between the latent trait and extraversion and between the latent-class variable and extraversion respectively. The category scores

and association parameters will be estimated in the model. Simulation research shows that the standard errors of the parameter estimates as well as latent class assignment can benefit substantially from incorporating collateral variables (Smit, Kelderman, & van der Flier, 1999, 2000).

Finally, assuming conditional independence of the self-disclosure responses $\mathbf{U} = (U_1, \dots, U_k)$ given the latent trait and latent class membership, one obtains from Equation 8,

$$\begin{aligned} \log P(\mathbf{U} = \mathbf{u}, \theta_x = \theta_x, Y = y, E = e) \\ = \lambda + \lambda_x + \lambda_y + \lambda_e + \sum_{u_i=1}^{m_i} \lambda_{u_i} + \sum_{u_i=1}^{m_i} \lambda_{u_i y} + \mu_e \phi^{XE} \theta_x + \nu_e \phi^{YE} \mu_y + \sum_{u_i=1}^{m_i} \mu_{u_i} \phi^{U_i X} \theta_x, \quad (9) \end{aligned}$$

where $\mathbf{u} = (u_1, \dots, u_k)$ are the values taken by \mathbf{U} . The sum $\lambda_{u_i} + \lambda_{u_i y}$ corresponds to the item difficulty parameter of the nominal response model as described in Equation 1, which may vary over latent classes. The item discrimination parameter of the model corresponds to $\mu_{u_i} \phi^{U_i X}$, where the association parameter $\phi^{U_i X}$ may vary over the items, and the category scores μ_{u_i} over the items and their categories.

If n_{ue} denotes the observed frequency of the manifest responses $\{u_1, \dots, u_k, e\}$, the log-likelihood of the model given by Equation 9 can be written as

$$\begin{aligned} L = \log \prod_e \prod_{\mathbf{u}} [P(\mathbf{U} = \mathbf{u}, E = e)^{n_{ue}}] \\ = \sum_e \sum_{\mathbf{u}} n_{ue} \log \sum_{v_x} \sum_y P(\mathbf{U} = \mathbf{u}, v_x = v_x, Y = y, E = e). \end{aligned}$$

If $\boldsymbol{\zeta}$ denotes the vector of independent parameters in the model shown by Equation 9, the maximum likelihood equations are obtained by solving

$$\frac{\partial L}{\partial \boldsymbol{\zeta}} = 0.$$

The maximum likelihood estimates of the model parameters are computed by means of the EM-algorithm (Dempster, Laird, & Rubin, 1977). In the E(xpectation)-step, the probabilities for the complete data matrix are estimated given the observed data and the parameter estimates. This is followed by the M(aximization)-step, where the log-likelihood for the complete data matrix is maximized to obtain new estimates for the model parameters. The algorithm is repeatedly applied until some convergence criterion is met.

If a model is a special case of another model and not on the border of the parameter space of that model, the difference in L^2 -statistics with the corresponding degrees of freedom, equal to the difference in degrees of freedom of both models, can

be used to compare the relative fit of the two models and to determine which of the two models has the best fit to the data (Goodman, 1979). In the case of comparing models with different numbers of latent classes, the information criteria should be used. This is done by comparing the well known AIC- (L^2) statistics of two models. The best solution, defined the lowest value of the AIC-statistics, will be chosen. Since the models may have local maxima, they are analysed several times with different sets of random starting values. All analyses are performed with the program ℓ EM (Vermunt, 1997).

METHOD

Subjects

A total of 1,113 subjects, 811 men and 302 women, were tested between October 1999 and February 2002 in connection with a personnel selection or a personal development program at a Dutch consultancy firm, dealing with organizational development and recruitment and personnel selection. The educational level attained by the subjects was that of high school and/or higher education. They were employed or applying for middle to upper level positions in the service providing industry; these are operational and commercial functions.

Instrumentation

Self-disclosure is measured by a Dutch computer-administered questionnaire (Blom, 1992) measuring self-disclosure with respect to four different categories of people: employee (U_1), colleague (U_2), superior (U_3), and customer (U_4). There are 40 items, 10 for each type of self-disclosure. The four subscales are parallel versions; they differ in who the other person is. Each item states a situation and gives two options describing different ways to react to the particular situation. One option describes the tendency to share feelings and opinions with the other person. The other option indicates the reverse. The subject has to indicate with which of the two options he/she agrees most on a 6-point scale. An example of an item from the aspect self-disclosure toward an employee is:

Due to repeated discussions about an important subject the relationship between you and one of your employees has deteriorated.

I During our contacts I avoid the subject as much as possible in order not to disturb our relationship even more.

II I mention the effect this conflict has on our relationship and suggest that we talk this out straight away.

Option I does not indicate self-disclosure with respect to the conversation partner, while Option II does. The reliabilities (values of Cronbach's alpha) of the

subscales vary between .63 and .72. The attention is focused on differences in the score pattern over the self-disclosure variables, not on differences in response patterns within each self-disclosure variable. Therefore, for each subject the four scale scores of the self-disclosure variables are used, describing self-disclosure toward the different categories of people. The scale scores had a range from 1 to 10, with the scores 1 and 10 occurring only in a small part of the sample. To prevent estimation problems, the scores 1 and 2 were combined. The same was done for the scores 9 and 10, to obtain 8 categories with a sufficiently large number of subjects in each category. The scale from 1 to 8 corresponds to not having the characteristic at all and having this characteristic to a high degree. The correlations among the four subscales are between .51 and .70.

The other measure of interest is extraversion (*E*). Extraversion is measured by nine items selected from the extraversion scale of the Dutch adaptation of the NEO-PI questionnaire (Hoekstra, Ormel, & de Fruyt, 1995). Each of the nine items consists of a statement for which one has to indicate the degree to which one agrees with it. There are five options: agree completely, agree, neutral, disagree and disagree completely. An example of an item of the aspect extraversion is:

I love having people around me.

The value of Cronbach's alpha of this scale is .80. Here, the scale score of extraversion is used as well, which is in accordance with the scales of the self-disclosure measures.

Analyses

First the model as formulated in Equation 9 will be analysed with different numbers of latent classes. Furthermore, when the number of latent classes that gives the best fit to the data is determined, it will be analyzed whether the associations between the responses, as modeled with the latent trait, are class specific, that is whether $\phi^{U_i X} \neq \phi^{U_j X}$. Finally, it will be examined whether the assumption of conditional independence of the latent trait and the latent class variable holds.

The first hypothesis implies that there should be more than one latent class. When the model with the best fit to the data includes a latent class variable with more than one latent class, it is demonstrated that subpopulations can be distinguished that have qualitative different response patterns. To determine whether the differences in response patterns with respect to the self-disclosure variables reflect differences in selectivity in self-disclosure, the characteristics of the latent classes have to be examined.

First, it will be examined how the self-disclosure responses are associated with the latent trait by looking at the association parameters, $\phi^{U_i X}$, and the category scores μ_{u_i} of the self-disclosure responses u_i . To characterize the latent classes, first the $\lambda_{u_i y}$ parameters will be examined. These parameters show the tendency to

self-disclose toward the different categories of people for each latent class. A positive value indicates a higher tendency to respond in the specific response category, compared to the other response categories of the same item. Next, the expected category scores of the self-disclosure variables with respect to the different categories of people, given someone's score on the latent trait and latent class membership, will be computed by,

$$E(\mu^{U_i} | \theta_X = \theta_x, Y = y) = \sum_{u_i=1}^{m_i} \mu_{u_i}^{U_i} P(U_i = u_i | \theta_X = \theta_x, Y = y), \quad (10)$$

where $P(U_i = u_i | \theta_X = \theta_x, Y = y)$ is computed from the estimated model shown by Equation 9 using elementary probability theory. The Model shown by Equation 10 describes the dependence of self-disclosure response i on the latent trait in each latent class.

To describe the patterns of expected category scores of the self-disclosure variables, given latent class membership,

$$E(\mu^{U_i} | Y = y) = \sum_{u_i=1}^{m_i} \mu_{u_i}^{U_i} P(U_i = u_i | Y = y), \quad (11)$$

is computed. Using Equation 11, each latent class can be interpreted in terms of the general degree of self-disclosure relative to the other latent classes, as well as by the patterns across the four self-disclosure variables. To compute the variance over these expected category scores over self-disclosure responses, let Z_i be a statistic computed for self-disclosure component $i \in K = \{1, \dots, k\}$, and $\mathbf{Z} = (Z_1, \dots, Z_k)$. Let $\text{Var}_K(\mathbf{Z})$ denote the variance over the set K of the elements of \mathbf{Z} , thus,

$$\text{Var}_K(\mathbf{Z}) = \frac{\sum_{i=1}^k (Z_i - \bar{\mathbf{Z}}_K)^2}{k-1}, \quad (12)$$

where

$$\bar{\mathbf{Z}}_K = \frac{\sum_{i=1}^k Z_i}{k},$$

is the mean taken over K . By substituting \mathbf{Z} in Equation 12 for each latent class, with a vector of four expected category scores of Equation 11, the variance of the expected category scores given latent class membership can be computed.

Hypothesis 1 stated that the different latent classes could be characterized by differences in the degree of selectivity in their self-disclosure. The degree of selectivity in self-disclosure depends on the subject's variability of self-disclosure responses toward the different categories of people. Therefore, the mean intra-person variance of each latent class will be computed, that is, the mean variance of the self-disclosure response patterns of the subjects belonging to each of the latent classes. If μ_u denotes a vector of four self-disclosure category scores ($\mu_{u_1}, \dots, \mu_{u_k}$), then the mean intra-person variance for each latent class is,

$$E[Var_K(\mu_u)|Y=y] = \sum_u Var_K(\mu_u)P(U=u|Y=y). \quad (13)$$

The latent class with the highest mean intra-person variance consists of subjects who are the most selective in their self-disclosure toward the different categories of people, compared to the other latent classes. It is expected that subjects who show a low degree of self-disclosure will be the most selective in their self-disclosure.

The second hypothesis implies that the latent class consisting of subjects who show a relatively high degree of self-disclosure will also attain a relatively high score on extraversion. It will be examined whether the latent class showing the highest tendency to self-disclose, as shown by $\lambda_{u_i y}$, will show the highest expected category score on extraversion, and vice versa. Furthermore, it is expected that the category scores of extraversion, μ_e , in the relation with the latent trait are non-decreasing. Spearman's correlation coefficient will be computed for the relationship between the intra-person variance and extraversion, to examine whether subjects with low variation in their response patterns are more extravert.

RESULTS

The results of goodness-of-fit testing of latent-trait latent-class model shown by Equation 9 with different numbers of latent classes are given in Table 1. The overall likelihood-ratio chi-squared statistics (L^2) and their degrees of freedom (df) are given, as well as the corresponding AIC-statistics (AIC). The differences in the fit-statistics of the subsequent models are given as well.

On examining which number of latent classes gives the best explanation of the structure of the data, the AIC-statistics were compared. These results suggest that the model with three latent classes has the best fit to the data and proves that a model with only the latent trait ($Y = 1$) is not sufficient to explain the structure of the data. It is demonstrated that subpopulations can be distinguished that have qualitative different response patterns, which is a first support of the Hypothesis 1.

TABLE 1
Fit Statistics of the Latent Class Analyses With a Discrete Latent Trait,
a Latent Class Variable and Five Manifest Variables, as Well as the
Differences Between the Models

<i>Model</i>	L^2	<i>AIC</i>	<i>df</i>	ΔL^2	ΔAIC	Δdf
1-Model with $Y = 1$ classes	4739.722	-60642.277	32691			
2-Model with $Y = 2$ classes	4658.809	-60663.191	32661	80.913	20.914	30
3-Model with $Y = 3$ classes	4546.593	-60715.407	32631	112.216	52.216	30
4-Model with $Y = 4$ classes	4515.954	-60686.046	32601	30.639	-29.361	30

Furthermore, it is examined whether the association parameter of model 3 should be class specific, that is whether $\phi^{U_iX} \neq \phi_y^{U_iX}$. Finally, model 3 with the addition of an association between the latent trait and the latent class variable is analyzed, to test the conditional independence of the two latent variables. Both models showed a solution on the boundary of the parameter space, indicated by a large number of zero estimated frequencies. As a consequence, the asymptotic distribution of the L^2 -statistics is no longer a chi-square distribution, and therefore, the fit-statistics of these models cannot be trusted. Consequently, model 3 was chosen as the best fitting model, where the latent trait and latent class variable can be considered to be independent.

Parameter Estimates

The probability of belonging to latent class one, .25, is the smallest. The probability of belonging to latent class two is .36, while for latent class three this is .39.

In Table 2, the results of the analysis of the associations between the latent trait and each of the self-disclosure variables are shown. The association parameters

TABLE 2
Category Scores, μ_{U_j} , and Association Parameters, ϕ^{U_jX} ,
of the Association Between the Latent Trait Variable
and the Self-Disclosure Variables

<i>Response Category</i>	U_1	U_2	U_3	U_4
1	-0.4625	-0.6399	-0.5648	-0.4189
2	-0.3071	-0.2193	-0.3350	-0.2759
3	-0.2841	-0.1218	-0.2312	-0.2515
4	-0.1460	-0.0263	-0.0767	-0.1945
5	-0.0393	-0.0175	0.0313	-0.0331
6	0.2504	0.1033	0.2780	0.1448
7	0.3584	0.2471	0.3315	0.2956
8	0.6301	0.6744	0.5668	0.7334
Association Parameter	217.7704	620.4701	122.7333	141.8184

correspond to the $\phi^{U_i X}$ parameter of Equation 9, where u_i is the response to item i which in this study is one of the four self-disclosure variables U_i . The item category scores correspond to the μ_{u_i} parameters of the same equation. It is expected that the ordering of the response categories, as described by the estimated item category scores, is non-decreasing.

The association parameters suggest that self-disclosure toward colleagues relates stronger to the latent trait than the other self-disclosure variables. The item category scores are non-decreasing as one responds in a higher response category. The results of Table 2 are depicted in Figure 2. This is accomplished by taking the product of the category scores and the association parameters.

It is assumed that measured self-disclosure has an ordinal association with the latent trait variable, which describes latent self-disclosure. It is seen in Table 2, as well as in Figure 2, that the relation between measured self-disclosure and the latent trait is non-decreasing. The higher one scores on the latent trait variable, the higher one also scores on the self-disclosure variables.

The term $\lambda_{u_i y}$ in Equation 9 describes the tendency to respond in a certain response category, given latent class membership. Table 3 shows the corresponding parameter estimates. The NE entries in Table 3 are not estimated; there is insufficient information in the data to obtain adequate estimates under the model.

It can be seen in Table 3, that latent class one is characterized by relatively high scores on self-disclosure toward the different categories of people. Subjects belonging to this latent class have a high tendency to show self-disclosure. The sec-

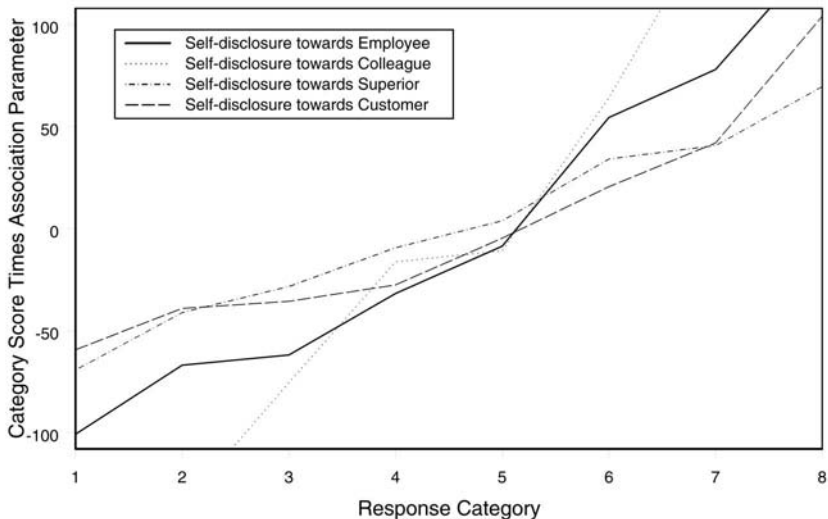


FIGURE 2 Category scores times the association parameter.

TABLE 3
Parameter Estimates of $\lambda_{u,y}$, Describing the Relation Between the Latent Class Variable and the Self-Disclosure Variables

Response Category	Class											
	1				2				3			
	U_1	U_2	U_3	U_4	U_1	U_2	U_3	U_4	U_1	U_2	U_3	U_4
1	-1.85	0.51	-0.22	-0.57	1.85	5.06	2.44	1.03	NE	-5.57	-2.22	-0.46
2	-1.46	-1.41	-0.93	-0.51	2.42	2.53	2.04	1.09	-0.96	-1.12	-1.11	-0.58
3	NE	-1.70	-1.19	-0.85	0.34	0.84	1.09	1.00	-0.34	0.87	0.10	-0.16
4	-1.47	-1.77	-1.62	-1.03	0.58	0.19	0.54	0.23	0.90	1.58	1.08	0.79
5	-0.29	0.20	0.15	-0.51	-1.07	-2.67	-1.34	-0.34	1.36	2.47	1.19	0.85
6	1.40	0.71	0.81	0.48	-2.37	-2.47	-1.84	-1.40	0.97	1.77	1.03	0.92
7	3.08	2.92	0.24	1.65	-3.08	-3.20	NE	-2.31	NE	0.28	-0.24	0.65
8	2.58	0.00	2.51	1.68	NE	NE	-2.44	NE	-2.58	NE	-0.07	-1.68

Note. NE = not estimable.

ond latent class indicates the opposite. It consists of subjects with relatively low scores on self-disclosure. Latent class three shows medium scores (between 4 and 6) on the self-disclosure variables.

The next three graphs, in Figure 3, describe the expected category score of the self-disclosure variables with respect to the different categories of people, given someone's score on the latent trait variable and given the class someone belongs to, as computed by Equation 10.

The graphs demonstrate that all latent classes indicate that the expected category scores of the self-disclosure variables are increasing as one scores higher on the latent trait. The results also indicate that subjects belonging to the second latent class have relatively low scores on the self-disclosure variables with respect to the different categories of people. The subjects are relatively closed; they do not show much self-disclosure to others. Subjects belonging to latent class three are not likely to attain extreme scores, except for self-disclosure toward colleagues at the lower end of latent self-disclosure. Latent class one consists of subjects who may attain high scores. These results are in agreement with those of Table 3.

Figure 4 depicts for each self-disclosure variable the expected category score given latent class membership. Each line indicates a different latent class. The expected category scores are computed as shown by Equation 11.

Figure 4 shows that the latent classes differ in their general level of measured self-disclosure and that the latent classes each have different response patterns with respect to self-disclosure toward different categories of people. The first latent class indicates a reverse pattern compared to the second latent class. Subjects belonging to the second latent class seem to be closed toward employees and superiors and relatively open toward their colleagues and, to a lesser extend, customers. The third latent class shows relatively high self-disclosure toward superiors.

Both the variance of the expected category scores, as well as the mean intra-person variance of the scores over the self-disclosure variables for each latent class were computed. The variance of the expected category scores over self-disclosure responses for each latent class describes the variance of the response patterns which can be seen in Figure 4. This variance is the largest for latent class two (.0022), which is twice as large as for latent class one, which has a variance of .0011. The variance of the expected category scores for latent class three is .0017. This indicates that latent class two is characterized by a response pattern with a relatively large variability over the expected category scores of all latent classes.

The mean intra-person variances shown by Equation 13 for the three latent classes are .0487, .0246, .0230 respectively. For latent class one, the mean intra-person variance is twice as large as the variances of the other two latent classes. This means that within latent class one, on average subjects have more variance in their response patterns, compared to the other latent classes, and therefore are the most selective in their choice to whom they will show self-disclosure. The mean intra-person variance for subjects belonging to latent class

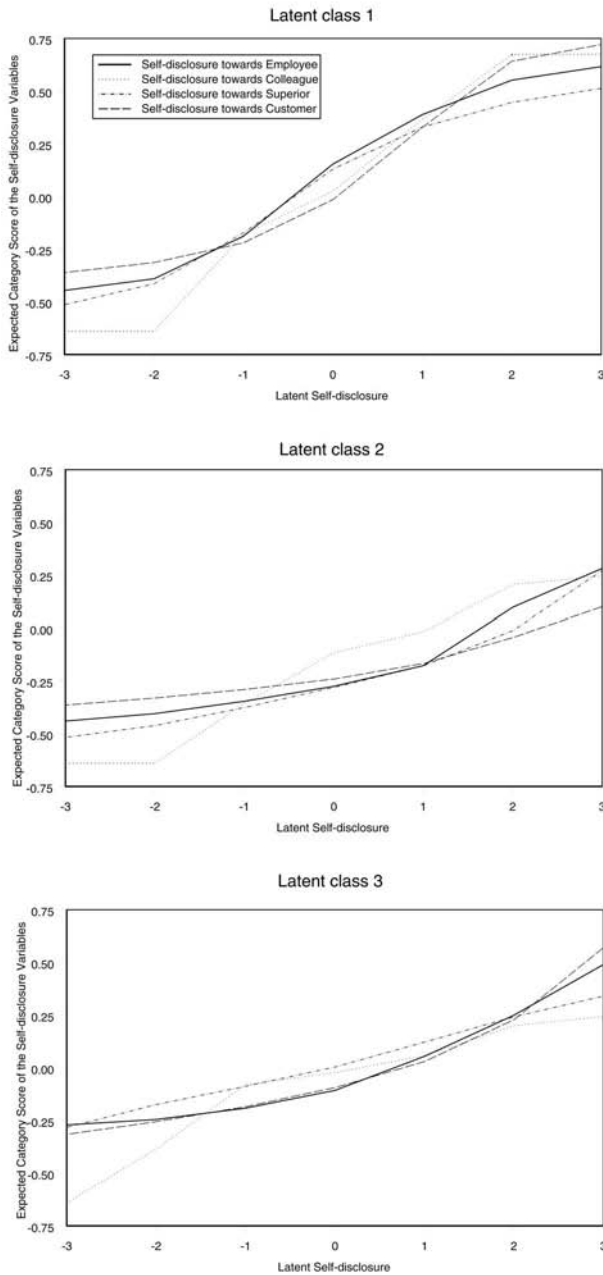


FIGURE 3 A graph for each latent class, describing the expected category score on measured self-disclosure with respect to the different categories of people as a function of the latent trait variable.

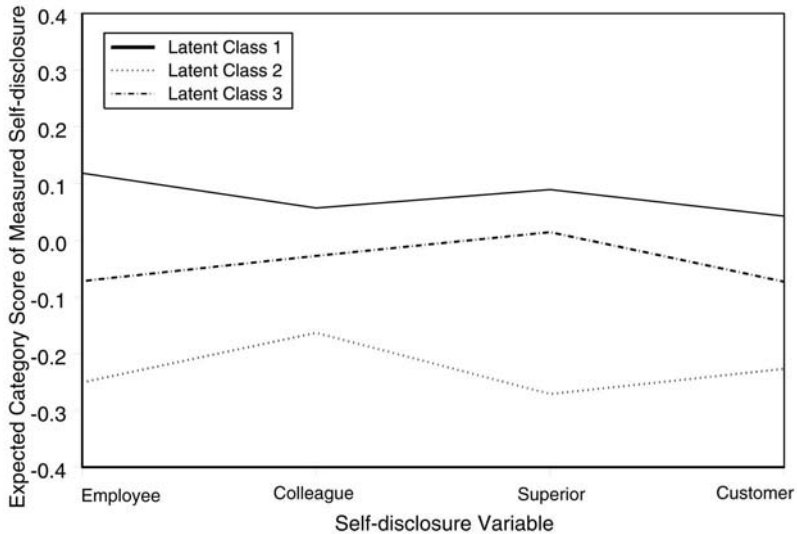


FIGURE 4 Expected category score on measured self-disclosure for each combination of a latent class and a self-disclosure variable.

two was relatively low. These subjects are not very selective in their self-disclosure and attain relatively low scores on self-disclosure, even though the variance of the expected category scores for this class was relatively high. The variable pattern of expected category scores shown by this latent class indicates that this latent class is a relatively homogeneous subgroup, consisting of subjects with relatively similar response patterns. It can be concluded that they are closed toward the different categories of people in the work environment.

Latent class one, on the other hand, is a rather heterogeneous subgroup. The subjects belonging to this latent class are relatively selective in their self-disclosure, which means that their degree of self-disclosure depends on the recipient of the self-disclosure. As the variance of the expected category scores for this latent class is relatively low, the response patterns of the subjects belonging to this latent class should be relatively different to each other, to create a flattened pattern of expected category scores of the whole group, with a low variance. The subjects themselves have more variable patterns than is shown by the pattern of their expected category scores showed in Figure 4. It is contrary to the expectations that latent class one consists of subjects with the largest differences in scores of self-disclosure toward the different categories of people. It means that they are relatively selective in their self-disclosure, compared to the other two latent classes, while it was expected that subjects with lower scores on self-disclosure would be the most selective in their self-disclosure.

Latent class three shows a low mean intra-person variance and a variance of the expected category scores which has a value in between those of the other two latent classes. Their expected category scores on the self-disclosure variables also lie in between those of the other two latent classes. Subjects belonging to this latent class are inclined to show a moderate degree of self-disclosure to others and are not very selective in their choice to whom they will show self-disclosure.

The latent classes differ in their general tendency to self-disclose. Furthermore, the latent classes can be characterized by qualitative different response pattern, which can be interpreted in terms of differences in selectivity in self-disclosure. This supports the first hypothesis. Next, the associations of the latent variables with the collateral variable will be examined.

Associations With Extraversion

The hypothesis concerning the associations between the latent variables and extraversion is tested. The difference between the L^2 -statistics of both models yields a test for the associations between extraversion and each of the latent variables, with degrees of freedom equal to the difference of degrees of freedom between both models. The AIC-statistics are given as well. The results of the models analyzed are shown in Table 4.

It is seen that the relationship between the latent trait variable and extraversion is significant, $L^2(7) = 31.307, p < .01$. This supports the hypothesis that there is an association between extraversion and the latent trait. The difference between Model 6 and Model 3 is also significant, $L^2(8) = 66.1795, p < .01$. This indicates that there is also an association between extraversion and the latent class variable. The AIC-statistics yield the same results.

Table 5 exhibits the category scores, μ_e , of the association between the latent trait variable and extraversion. The association parameter, ϕ^{XE} , has a value of 29.5226. Extraversion was expected to be a non-decreasing function of the latent trait variable.

However, the category scores of Table 5 cannot be described as non-decreasing as one scores higher on extraversion.

TABLE 4
Results of the Analyses of the Best-Fitting Model and the Same Model
Without the Association Between Extraversion and Each
of the Latent Variables

Model	L^2	AIC	df
3-Model with $Y = 3$ classes	4546.5930	-60715.4070	32631
5-Model 3 without association between extraversion and θ_X	4577.9000	-60698.1000	32638
6-Model 3 without association between extraversion and Y	4612.7725	-60665.2275	32639

TABLE 5
Category Scores, μ_e of the Association Between the Latent Trait Variable
and Extraversion

Response Category	1	2	3	4	5	6	7	8
Category score	-0.3257	-0.5841	-0.1416	0.1935	-0.1469	0.4492	0.0354	0.5202

The expected category scores on extraversion in the three latent classes are .0624, -.1257, and .0272, respectively. The latent class showing the highest degree of observed self-disclosure (Latent Class 1) also has the highest expected category score on extraversion, and the latent class showing the lowest observed self-disclosure (Latent Class 2) also shows the lowest expected score on extraversion. This supports the hypothesis that subjects who will show more self-disclosure are more extravert compared to subjects showing less self-disclosure. This association however cannot be described as non-decreasing on an individual level (2a).

Finally, Spearman's correlation coefficient is .021 for the relationship between the intra-person variance over self-disclosure variables (selectivity) of the subjects in the sample and their score on extraversion. This association is not significant, $p > .05$. Thus, the hypothesis that more extravert subjects are less selective in their self-disclosure is not supported (2b).

CONCLUSION AND DISCUSSION

The results showed that the model with a latent trait variable, and a latent class variable with three categories has the best fit to the data. The four self-disclosure variables appear to be increasing functions of the latent trait, as they should be. The higher one scores on the latent trait, the higher one also scores on the self-disclosure variables.

Next, the relation between the latent class variable and the self-disclosure variables was examined. Subjects in the latent classes differ in their general tendency to self-disclose, as well as in the patterns of the scores on the self-disclosure variables. The differences in patterns could be interpreted in terms of differences in selectivity in self-disclosure, where the first latent class appeared to consist of subjects who are relatively the most selective in their self-disclosure.

When extraversion was examined, the results indicated that both latent variables have an association with extraversion. The relation between the latent trait and extraversion could not be described as a non-decreasing function. The hypothesis that subjects who are the most selective in their self-disclosure would have the lowest scores on extraversion was not supported.

Summarized, the results indicate that qualitative as well as quantitative aspects of self-disclosure can be identified. On top of self-disclosure as a general personal-

ity construct, selectivity in self-disclosure appears to play a part in the process of self-disclosure. Subjects in different latent classes differ in their general tendency to self-disclose and have different response patterns of measured self-disclosure. The importance of the notion that it may matter whom someone is facing in deciding whether to show self-disclosure or not was demonstrated. The aspect of situational specificity may become an extension of the literature on self-disclosure.

One of the first studies on self-disclosure, by Jourard and Lasakow (1958), found differences in self-disclosure toward different target-persons, like toward the mother, father, or friends. A study by Slobin, Miller, and Porter (1968) on self-disclosure at four organizational levels, indicated that subjects showed the greatest self-disclosure toward their colleagues. Furthermore, Slobin et al. found more willingness to self-disclose toward superiors than to disclose toward employees. The second latent class, consisting of relatively closed subjects, showed a relatively high degree of self-disclosure toward colleagues, compared to the other categories of people, which is consistent with the first result of Slobin et al. Regarding self-disclosure toward superiors, the stated pattern only emerged in latent class three, where self-disclosure toward superiors is even greater than disclosure toward colleagues. A possible explanation for the relatively high self-disclosure willingness toward superiors is that disclosure to a superior may be seen as an ingratiating strategy. This implies that subjects on a lower level in the organizational hierarchy disclose more to people with a higher status, with the hope of reciprocal self-disclosure. This in turn, would equalize their status (Slobin et al., 1968). In the first latent class a relatively high degree of self-disclosure toward both superiors and employees was observed. This pattern clearly deviates from the findings of Slobin et al. by revealing a relatively high degree of self-disclosure toward employees.

Selectivity in self-disclosure may reflect different motives. Miller and Read (1987), as well as Omarzu (2000), proposed that the decision to self-disclose in a given situation may depend on the goals that an individual wants to attain. For the people belonging to latent class two, who appear to be closed and relatively consistent in their self-disclosure, self-disclosure may not be the preferred strategy to attain their goals. In latent class one on the contrary, self-disclosure is probably seen as a way to attain goals. These differences may also be related to differences in interpersonal trust and the perceived risk of self-disclosure (Steel, 1991). A high perceived risk of self-disclosure may have led the subjects of latent class two to decide not to show self-disclosure. Apart from examining whether people differ in their self-disclosure toward different categories of people, it is also shown that people differ in the degree to which they are selective in their choice to whom they will show self-disclosure. What the reasons are that people differ in the degree of selectivity in self-disclosure, and whether status, trust, or the subjective view of the risk of self-disclosure are related to that, is something which may be studied in further research.

A limitation of this study is that self-disclosure was measured toward others who all have to do with the work environment. Although its relationship to the stable personality trait extraversion suggests that the general tendency to self-disclose can be generalized to other situations, the patterns of self-disclosure are specific to the work environment. People may show relatively little self-disclosure in their work environment but might respond differently in other environments, like home. In a home situation, where people can feel safe and free, it can be expected that people will have less difficulty to show self-disclosure. They are among the people closest to them. Measures of self-disclosure toward other categories of people could provide more insight in this issue.

Mixture measurement modeling provided a useful method to study quantitative differences, differences in the general degree of self-disclosure, as well as qualitative differences in self-disclosure toward the different categories of people. In this way, application of a mixture measurement model contributes to research on construct validation. Furthermore, it may lead to a better prediction of disclosure behavior in general as well as in specific classes of situations. It is possible to examine whether, apart from a general personality construct, different patterns of responses can be distinguished.

The proposed latent-trait latent-class model can be used to allocate subjects to the different latent classes and to determine their score on the discrete latent trait. From sample data, the probability of belonging to each of the latent classes and attaining a certain score on the latent trait, can be estimated from the subjects' manifest responses. The class someone belongs to is usually chosen as the class with the highest conditional probability given his or her manifest response pattern. The probability of each combination of the latent variables, given the responses u_1 through u_4 , is

$$\pi_{\theta_x y | u_1 u_2 u_3 u_4} = \frac{\pi_{\theta_x} \pi_y \pi_{u_1 | \theta_x y} \pi_{u_2 | \theta_x y} \pi_{u_3 | \theta_x y} \pi_{u_4 | \theta_x y}}{\sum_{\theta_x} \sum_y \pi_{\theta_x} \pi_y \pi_{u_1 | \theta_x y} \pi_{u_2 | \theta_x y} \pi_{u_3 | \theta_x y} \pi_{u_4 | \theta_x y}}.$$

Based on the conditional probabilities of the manifest variables given the values of the latent variables, and the probabilities of the latent variables itself, the probability can be computed of each combination of the latent variables, given the manifest responses. In this way it is possible to determine both the subject's degree and type of selectivity in his self-disclosure.

Self-disclosure is a difficult concept, because it involves both qualitative and quantitative aspects. This research showed that it is possible to identify both aspects. It may help in providing us with a better understanding of self-disclosure, and when and why people differ in their degree of self-disclosure toward different people. This research also illustrates the possible use of latent-trait latent-class models for the analysis of differences in item responses between subjects.

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